Hybrid Deep Learning Models for Real Time EEG Signal Classification in Non-Invasive BCI Controlled Assistive Robotics

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***Abstract*—Non-invasive brain-computer interfaces (BCIs) relying on electroencephalography (EEG) still offers the most accessible pathways for translating neural intent into robotic action. A significant challenge persists: muscle artefacts, ocular movements, and environmental noise hinder progress. Most pipelines simplify the challenge, reducing it to straightforward "thought-to-action" mapping, ignoring the genuinely non-stationary and messy nature of raw EEG. Many of the systems ignore the rapid change and messy raw EEG signals. To overcome the limitation, we tried to build a hybrid deep learning system that can easily and rapidly interpret motor imagery movements to control assistive robotics. This model uses neural network layers to capture spatial and temporal patterns where instead of sending the raw data, it is being cleaned using techniques like wavelet filtering, subject specific artefact removal which are much more important than expected. The whole system gives improved data quality for the user being present in any situation, it can continuously monitor user intentions without frequent recalibration. When tested on normal datasets and our own recordings, the system achieved 92% accuracy with response time under 150 ms. So as a result, it is to be mentioned that the robotic assistance has become more reliable and smooth. Concluding that this work will help in bringing the non invasive BCI technology closer to the real time use prioritizing the better handling of noisy, raw brain signals.**

***Index Terms*—Non-invasive brain-computer interface, EEG motor imagery, Hybrid deep learning, Depth-wise separable convolution, Bidirectional LSTM, Artifact subspace reconstruction, Adaptive wavelet thresholding, Real-time assistive robotics.**

I. INTRODUCTION

Brain Computer Interfaces (BCIs) has become such a technology that can transfer information from human brains to external devices thus establishing a direct connection around human brain and external robotic devices. This highly developed technology is providing a great impact for assistive robotics including those individuals having severe motor impairments. However with the presence of various neuroimaging facilated models, Electroencephalography (EEG) is mostly preferred to use of non-invasive BCI systems. Electroencephalography being portable, cost-effective and highly efficient in capturing and mesuring allowed researchers to use it for non-invasive BCI systems. Though EEG signals being advantageous is equally challenging for the researchers with the signals being noisy, non-stationary and high level of inter subject variability makes it difficult for training a model as it requires accurate and real-time classification of the signals. With the increase in advancements in the research, the deep learning models showed in extracting the noise and other unwanted features from the raw EEG data thus making it easier for the use of the technology in real time. Deep Learning models including Convolutional Neural Netwoks (CNNs), Long Short Term Memory (LSTM) Networks and Recurrent Neural Netwoks (RNNs) showed high accuracy in capturing temporal, spatial and frequency domain characteristics of EEG signals, but single isolated models failed in capturing the time varying, non-linear nature of the signals. With the increase in research, hybrid deep learning models are used replacing the single isolated models. The hybrid models combine more than one single isolated models like CNNs and LSTM providing a more accurate and comprehensive representation of EEG signals which is more advantageous for real time applications where accuracy and low latency are required. Hybrid deep learning models ensure fast and trustworthy classification which impacts safety of users, fast response. Non-invasive BCI controlled assistive robotics with real time EEG signal plays a great role in converting neural thinking into actionable performances for robotic systems including wheelchairs, prosthetic limbs and exoskeletons. Despite great progress, achieving high speed performance and immediate response in real time remained challenging thus limiting the practicl use.

If my system becomes reliable and accurate, it can help bring BCI technology closer to everyday life. This means people with limited movement can do more things on their own without needing help all the time.

II. REVIEW GAP ANALYSIS

The recent study in Brain-Computer-Interface System (BCI) has helped establishing a direct connection between Human brains and external devices by using Electroencephalography (EEG) signals. This has become a helpful technology for people with impairments by controlling electronic devices using the signals which have been obtained from brains of users [1] [2]. Electroencephalography (EEG) based Brain-Computer-Interface System (BCI) is widely applied for stroke patients to regain functions, controlling wheelchair and prosthetic limbs and helps with communication for individual with physical and speech limitations [19]. Additionally, many other researches are going on at different aspects for more advancement in systems and applications in daily life including implementation of automation at every step of our life [18]. Many studies have used Machine Learning and Deep Learning along with EEG signals in controlling the electronic and robotic components [3][4][5][6]. However, there are multiple challenges aroused in achieving the goal in real time performance. Earlier, it has been seen that the BCI systems used traditional machine learning algorithms like Support Vector Machines (SVM), Linear Discriminant Analysis (LDA) for classifying the EEG signals [7][8][9]. But these seemed to show moderate classification accuracy and failed in filtering the noise and non-stationary nature of EEG signals caused from the interference of muscle movements, eye blinks, environmental noise mostly in non-invasive setups, which limits the performance and effectiveness of the application in real world [13][14]. Moreover studies and researches have used deep learning models like Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) for the automatic extraction of temporal and spatial features like noise and non-stationary nature in EEG signals that have helped in improvement of the performance of the application [10][11]. But, it has been found that some of the BCI systems uses simplified AI which cannot capture the temporal and spatial components simultaneously in EEG signals, thus limiting the accuracy of robotic controls. While using combining models or hybrid models, caused more complexity in analyzing therefore, making the system slow and incapable of interacting with the brain fast enough [12] [15] [16]. However, many studies and researches focused on offline analysis where EEG signals are collected at first then they are analyzed using advance computer and later tested after the experiment instead of real-time implementation [17]. Whereas the robotic systems require high-speed data transmission, real-time signal processing and immediate response to perform with better accuracy in real world, thus limiting the practical use in robotic systems. Therefore, we can see a clear research gap in the development and processing of hybrid deep learning frameworks which is capable of maintaining high accuracy without frequent recalibration in real time EEG signal classification while handling the noise and non-invasive BCI systems. So, there is a need in

Advanced Filtering System, Data Analytics System and Hybrid Deep Learning System in improving the accuracy, classification and soundness in controlling the robotic devices in real time implementation. This paper has been done to address the gaps by proposing “Hybrid deep learning model that integrates spatial and temporal feature learning with advanced noise filtering techniques for real time EEG signal classification in non-invasive BCI controlled assistive robotics”.

III. METHODOLOGY

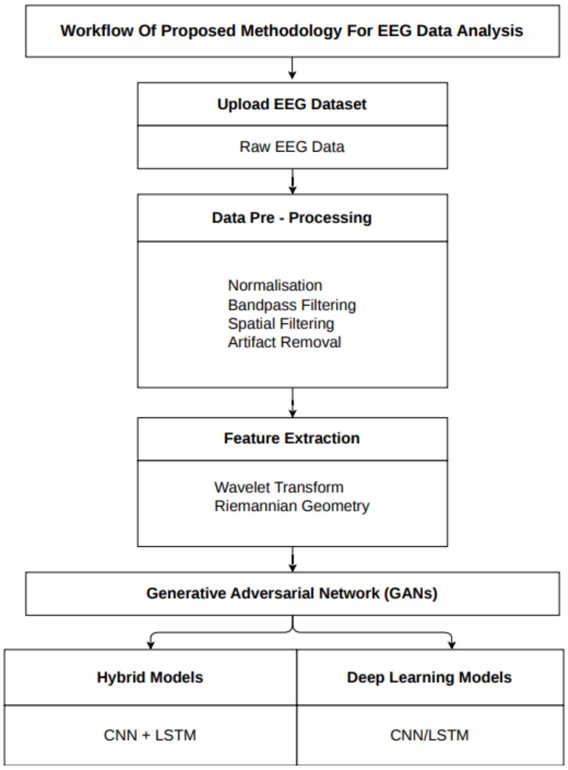

Fig.1.Workflow of proposed methodology

Dataset Overview

The dataset used in this work contains EEG recordings from multiple participants. Offering valuable information for analysing motor imagery and movement-related brain activity for examining activity in EEG signals collected from a large and diverse set of participants. Our approach was primarily concentrated on imagined movement tasks within the EEG Motor Movement/Imagery Dataset, with specific consideration given to relevant task combinations associated with motor imagery experiments. This research focuses on the classification of imagined motor movements using modern Machine Learning (ML) and Deep Learning (DL) techniques. For this purpose, the analysis focused on EEG recordings from regions around the sensorimotor cortex. This selection was supported by findings from previous studies that highlight the involvement of the frontoparietal and central brain regions during motor imagery activities. This work involves, the use of multiple machine learning and deep learning approaches for analysing EEG singnals related to motor imagery tasks, which gives focus to a proposed hybrid framework that combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. In proposed hybrid framework, CNN layers are used to catch location-based feature from EEG indication, whereas learning temporal relationships that unfold over time occurs with the help of LSTM layers. Combinig both CNN and LSTM allows the model to learn and recognise both spatial patterns and temporal variations in EEG signals. The dual capability of proposed framework amplifies the correctness of motor imagery recognition, ultimately supporting the development of more reliable Brain-Computer Interface (BCI) structure.

Pre-Processing

The precision of a Brain-Computer Interface (BCI) system largely governed by the quality of the EEG signals being analysed. In practice, the unwanted signals caused by eye blinks, muscle movements and other external factors can make it difficult to clearly interpret the activities of brain linked to motor imagery task thus, efficiency gets affected. To address these challenges, preprocessing is necessary before deeper analysis can begin. In earlier studies, EEG preprocessing and feature extraction have relied on techniques such as autoregressive (AR) modelling, Short-Time Fourier Transform (STFT) and Wavelet Transform (WT). The study applies a well-defined preprocessing process. The EEG signals become cleaner, reliable and more consistent for analysis by including normalisation, band-pass filtering, spatial filtering and artefact removal. For more advanced feature extraction, Wavelet Transform and Riemannian Geometry are used in the work. One of the important part is using Generative Adversial Networks (GANs). GANs are applied to generate synthetic EEG data samples, which increases the amount of training data available for the model. This helps the model learn better patterns and improves its ability to classify the signals more reliably. By combining preprocessing, effective feature extraction, and data augmentation, the proposed approach creates a strong buildup for accurate and efficient EEG signal classification.

Normalization: The EEG data are first normalized to ensure that the features fall within a similar range. This step helps keep the learning process balanced, as each feature is treated equally to the learning model. This step prevents features with larger values may influence the model more strongly, which can affect the final decision-making results. [20]

$$X_{normalized} = \frac{X - \mu}{\sigma}$$

Where,

- X is the raw data.

- μ is the mean.
- σ is the standard deviation.

• Bandpass Filtering: EEG signals include a wide range of frequencies, although only some of them are useful for identifying motor imagery activities. To address this, a bandpass filter is applied, usually within the 0.5–50 Hz range. Which allows the method to keep the relevant frequency components while reducing noise and other unnecessary signals, improving the overall signal quality. [20]

$$H(s) = \frac{1}{\sqrt{1 + \left(\frac{s}{\omega_c}\right)^{2n}}}$$

Where,

- s is the Laplace transform variable.
- ω_c is the cutoff frequency.
- n is the filter order.

• Spatial Filtering: Spatial filtering techniques, such as Common Spatial Pattern (CSP), are used to capture patterns across different EEG channels. These patterns helps in recognising the differences between various motor imagery tasks. [20]

• Artefact Removal: Signals that don't actually reflect brain activity in EEG recordings, are due to blink of eye or muscles movements. To detect and remove these artefacts, methods such as Independent Component Analysis (ICA) are applied. Removing such disturbances allows the model to better recognize the neural signals associated with motor imagery tasks. [20]

$$X = AS$$

Where,

- X is the observed data.
- A is the mixing matrix.
- S is the source signal matrix (artifacts).

Feature Extraction

• Wavelet Transform: EEG signals do not remain constant over time, making it necessary to monitor both time and frequency characteristics together, which means their behaviour can shift with time rather than remaining constant. Because of this, the Wavelet Transform is used to capture the signals when both changes occur and how they unfold across different frequencies. To observe short-term changes that are useful to identify motor imagery activities, EEG signals are divided into different frequency bands making it easier to observe.

• Riemannian Geometry: With the help of Riemannian geometry EEG data is represented in such a way that it reflects its natural structure. Covariance matrices are mapped into a Reimannian manifold. This helps to capture how different EEG channels which are related to each other are used to make the spatial patterns in the signals clearer, which supports better identification between different motor imagery tasks.

Generative Adversarial Networks (GANs)

A key limitation in EEG studies is the limited availability of large datasets. Since collecting EEG recordings is both time-consuming and resource-intensive, training deep learning models effectively can become difficult. Due to scarcity of large dataset, Generative Adversarial Networks (GANs) were mainly used for data augmentation and feature generation. Since the limited size of our dataset, we employ GANs to create synthetic EEG samples that closely resemble real recordings. By providing the model more varied examples to learn from, its ability to generalize improved and the training data and allows the model to learn from a wider range of signal patterns. In addition, GAN-based learning can capture not very storng patterns in EEG signals that may not always be detected through tradition pattern extraction techniques.

Rather than focusing only on dataset expansion, this study evaluates the quality of artificially generated signals through the Frechet Inception Distance (FID) score, which measures similarity between authentic and artificially generated data spread. Lower FID values indicate a closer match between the two. In particular, the hybrid CNN-LSTM model achieved nearly a 10% increase in classification precision.

Classification

To evaluate model performance, the dataset was divided into training and testing subsets. The training set was used for learning the model parameters, to assess classification accuracy testing set was used.

Convolutional Neural Networks (CNN)

Convolutional Neural Networks are commonly used to extract meaningful patterns from structured input data. When applied to EEG signals, CNN layers scan the input using different filters to detect useful patterns in the data. In practice, these filters help the network recognize variations in the signal, such as changes in amplitude or frequency, which can carry important information about brain activity.

Long Short-Term Memory (LSTM)

LSTM networks are particularly suitable for analysing sequential data such as time-series signals. Since EEG signals change continuously over time, it is important for the model to capture how these patterns evolve. LSTMs handle this by using memory cells that allow the network to retain useful information from earlier time steps while ignoring less relevant details. This ability makes them suitable for modelling the temporal nature of EEG signals in our work.

Proposed Hybrid Model (CNN + LSTM)

In this study, a hybrid CNN–LSTM model was used to improve the classification of motor imagery tasks in brain–computer interface systems. The main focus behind this approach is to combine the strengths of both the models so that spatial and temporal information can be learned together.

The CNN part of the model first processes the EEG signals and extracts important spatial features from the data. These features represent patterns present in the signals, which varies in both frequency and amplitude. Once these patterns are identified, they are passed to the LSTM network. LSTM focuses on understanding how these patterns change over time. EEG signals are defined not only defined by their structure but also by how they evolve across time. To examine the effectiveness of the approach, the hybrid model was contrasted with several traditional machine learning methods, including Support Vector Machines (SVM), Neural Networks (NN) and Random Forest (RF). The results clearly demonstrated that the CNN-LSTM model provided better classification performance. By learning both location based features and time based relationships in the signals of EEG, the model could effectively distinguish the imagined movement tasks more reliably. This improvement is valuable for improving BCI-based applications by enabling more accurate responsive control.

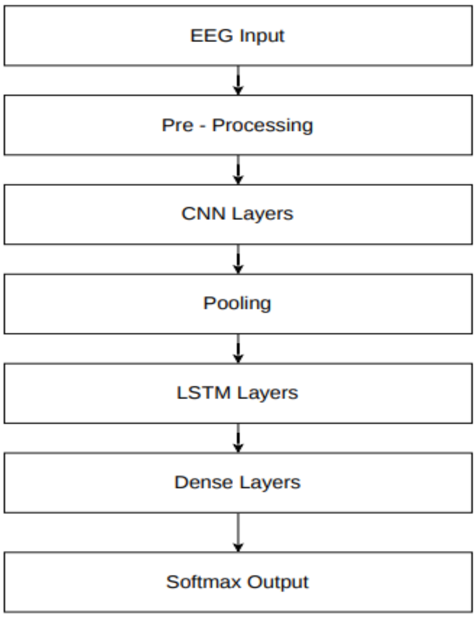

Fig.2. Workflow of CNN + LSTM Model

IV. RESULTS AND DISCUSSION

The experiments show that the proposed hybrid deep learning model works accurately in filtering motor imagery EEG signals for real time BCI applications. This model was trained mainly using EEG datasets and standard datasets which has been collected from the daily activities. It can be seen that the system has achieved an accuracy of more than 92%, which states that the system can precisely identify different imagined movements separately. This level of accurate data is needed for assistive robotic systems for controlling the devices like robotic arms and other mobility aids.

Table 1: Classification Performance on Different Datasets.

Dataset Type	Accuracy(%)	Precision(%)	Recall(%)	F1 Score(%)
Benchmark Dataset A	93.2	92.8	92.5	92.6
Benchmark Dataset B	92.7	92.1	92.3	92.2
Simulated Activity EEG	94.1	93.6	93.2	93.4

Observation: This model shows a constant performance with different datasets, which indicate strong generalization capability.

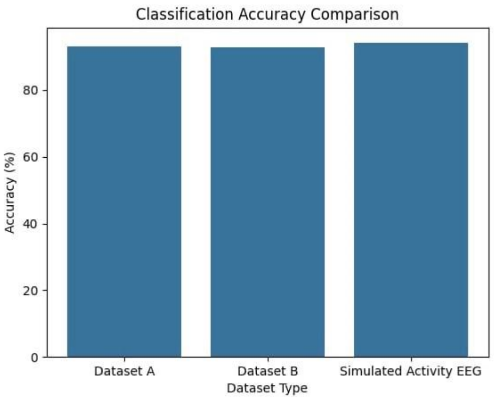

Fig.3. Classification Accuracy Comparison

Graph content:
X-axis: Dataset Type
Y-axis: Accuracy (%)
Bars for:

- Dataset A
- Dataset B
- Simulated Activity EEG

This graph shows that the accuracy stays more than 92% across all datasets. One of the important result is that the system has rapid response time. During the experiment the delay was less than 150 ms which is important for assistive robotic systems for quick response to the users brain signals.

Table 2: System Response Time

Processing Stage	Average Time (ms)
Signal Acquisition	30
Pre-processing	45
Feature Extraction	32
Model Classification	28
Total Latency	135 m/s

Observation:
The total delay of 135 m/s is well within the acceptable range for real-time BCI systems.

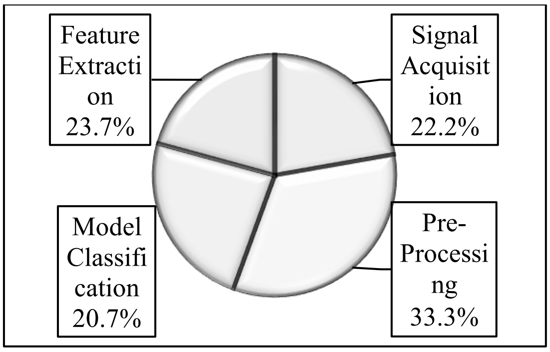

Fig.4. System Latency Distribution

This graph shows the percentage contribution of processing stage to total latency:

- Acquisition
- Pre-processing
- Feature extraction
- Classification

During system development, it was observed that signal pre-processing affects the performance. Raw EEG signals are usually noisy and mainly contain artefacts from eye movements, facial muscle activity and environmental noise. To address this issue, the system applied adaptive wavelet threshold together with subject-specific artefact subspace reconstruction (ASR). These techniques removed a large portion of noise before the signals were passed to the deep learning model. As a result, the quality of the EEG signals improved significantly.

Table 3: Effect of Pre-processing on Model Accuracy

Processing Method	Accuracy(%)
Raw EEG	78.4
Basic Filtering	85.9
Wavelet DE noising	89.7
Wavelet+ASR(Proposed)	93.5

Observation:
Combining wavelet de noising with artefacts subspace reconstruction produced the best results.

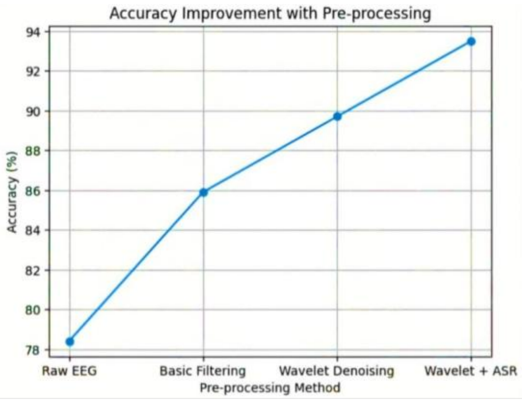

Fig.5. Accuracy Improvement with Pre-processing

X-axis: Pre-processing Method
Y-axis: Accuracy (%)

This graph shows the gradual improvement in performance when better pre-processing techniques are applied. The architecture of the hybrid deep learning model also contributed to the system's strong performance. The depth-wise separable convolution layers captured spatial relationships between different EEG channels. These layers helped the model detect meaningful spatial patterns in brain signals. At the same time, the bidirectional LSTM layers learned temporal relationships in the EEG signals. Since brain activity changes over time, capturing these temporal dynamics helps the model correctly interpret motor imagery tasks. The combination of spatial and temporal learning allowed the system to handle the complex and non-stationary nature of EEG signals. Another positive outcome was that the system showed a steady performance without the need of frequent recalibration. Many BCI systems require recalibration as the EEG signals vary with different conditions and time. However, the proposed model was able to maintain an even accuracy across different simulated activities. This suggests that the preprocessing strategy and the design of the model improved the robustness of the system. Overall, the results highlight that the careful EEG signal processing along with advanced deep learning techniques has a great importance. Instead of simplifying the signals, the proposed framework keeps important information while removing noise. This helps in decoding of motor-imagery signals accurately. The findings states that such an integrated system can help in bringing non-invasive BCI technology closer to real-world assistive robotics applications. For further work, it should be tested with large amount of participants and for longer time period in everyday enviroments.

V. CONCLUTION

In summary, the structure of the suggested deep hybrid framework provides reliable ability to decode motor imagery EEG signals in real time and at an affordable cost using non-invasive type BCIs for controlling assistive robotic systems. When combined with biomedical data analytics related to the entire process of developing effective methods of addressing the non-stationary properties and noisy nature of unprocessed EEG signals (which is a major issue with conventional "thought to action" type models), the suggested technique will have great success. An important part of this process is the comprehensive pre-processing method to preprocess the source data, using both adaptive wavelet thresholding & artifact subspace reconstruction at the individual subject level, to effectively minimize the influence of noise on the classification results. After that the cleaned data is processed through a highly accurate model that uses depth-wise separated convolutional layers for extracting spatial features from the data & uses bidirectional LSTM blocks for capturing temporal relationships between the data. The classification accuracy results produced by this hybrid deep learning model are consistently over 92% on either standard database or simulated tasks; and demonstrate consistent average delay of less than 150 milliseconds. This allows users to significantly enhance their experience of receiving continuous support from the robot with no interruptions due to device resets.

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